Journal of Applied Research on Industrial Engineering

www.journal-aprie.com

J. Appl. Res. Ind. Eng. Vol. 12, No. 1 (2025) 16–35.

Paper Type: Research Paper

Analyzing Consumer Behavior and Shopping Preferences using Bootstrap Aggregated Neural Regressor

Gurunadham Redapangu[1,*], Varre Buchi Narsimha[1]

[1] Department of Computer Science and Engineering (IT), University College of Engineering (A), Osmania University, Hyderabad, India; guru9nadham@gmail.com; vbnarasimha@gmail.com.

Citation:

Received: 10 August 2024 *Revised: 16 October 2024* *Accepted: 24 December 2024*	Redapangu, G., & Narasimha, V. B. (2025). Analyzing consumer behavior and shopping preferences using bootstrap aggregated neural regressor. *Journal of applied research on industrial engineering, 12*(1), 16-35.

Abstract

Now, the comprehension of consumer behavior and buying preferences is vital for the development of the global marketplace. The complex and non-linear correlations in the consumer data were unable to be captured by the conventional Logistic Regression (LR) models. Hence, the prediction of various behaviors is difficult. Through the introduction of the Bootstrap Aggregated Neural Regressor (BANR) model, the challenge related to accurately analyzing and consumer behavior prediction was effectively addressed in this study. To overcome the limitations of existing methods, as it fails to comprehend consumer preferences, it is considered to be the main objective of the study. Several lightweight Neural Networks (NNs) trained with bootstrap sampling and Adversarial Training (AT) were employed by the BANR model. By integrating Meta-Learning and AT, consumer behavior was effectively and accurately comprehended, and a robust result was offered by this proposed method. With a high True Positive (TP), high True Negative (TN), and low False Positive (FP) and False Negative (FN), the suggested BANR model attains a remarkable accuracy of 99.28%, and the experimental outcomes revealed it. A value of 0.99 was attained by the following: precision, recall, and F1 scores. The ability of the BANR model enhanced the accuracy and reliability of consumer behavior prediction, and the valuable implications for hyperlocal marketing strategies in the business field were offered by this model.

Keywords: Buying preferences, Consumer behavior, Bootstrap aggregated neural regressor, Hyperlocal marketing, Meta-learning techniques, Adversarial training.

1 | Introduction

Nowadays, better comprehension regarding consumer behavior and buying preferences is vital for business growth in the global marketplace [1]. Many businesses employ broad marketing strategies and online shopping development demands for consumer preferences comprehension, and it is significant. Then, Data Analytics (DA) and Machine Learning (ML) models are developed to address this problem.

Corresponding Author: guru9nadham@gmail.com

https://doi.org/10.22105/jarie.2024.472692.1656

One of the difficult tasks is analyzing consumer behavior. Large amounts of data in Data Collection (DC), data processing, and data analysis may result in technological risks. Increasing data volumes and diverse data sources make this problem more difficult [2]. Consumer preferences are changing continuously, so the data needs to be constantly updated. Effectively managing large amounts of data and consumer behavior comprehension was unable to be handled by conventional methods. The existing methods failed to address those challenges by conventional methods because the conventional methods may also have some challenges [3].

So, this framework demands sophisticated models and unique models. The patterns in consumer behavior can be predicted and monitored by employing ML and Deep Learning (DL) models [4]. In real-world consumer data, the complex and non-linear patterns were rarely captured by conventional methods like Decision Tree (DT) or Logistic Regression (LR). To customize strategies and products effectively, understanding consumer behavior is essential, and it is considered an issue for businesses. The application of these approaches will result in overfitting or underfitting, inability to respond to shifting preferences quickly, and problems related to high-dimensional datasets.

A new framework, BANR, was suggested in this study to address this issue. By employing AT methods and Bootstrap sampling and depending on several lightweight Neural Networks (NNs), this framework offered an accurate and effective outcome. Through the application of various sampling techniques and meta-learning, this framework becomes more robust. The suggested BANR framework facilitates analyzing consumer behavior and buying preferences effectively. The application of AT, meta-learning, and advanced NN structures will result in more accurate and reliable outcomes. This BANR model will play a vital role in improving marketing strategies and business decisions.

2 | Literature Survey

A novel platform was suggested by Wang [5] to accomplish several sales forecasting-related tasks. Retail sectors such as supermarkets, hypermarkets, and convenience shops are highly interconnected with a nation's economic condition as they cater to the basic requirements specified in Maslow's Hierarchy of Psychological Requirements. These retail divisions compete with one another within client groups and offer different product categories. This study proposes a new platform for obtaining sales forecasts by identifying financial indicators and their time lags, using ML and deep training approaches. Additionally, it estimates sales balances, considering the dynamic interconnections among different retail sectors and rival firms. Experiment results show that seasonal considerations only matter for hypermarkets, and the retail task population, real pay, and the consumer price index concurrently influence the sales revenues of the three retail divisions. In contrast to overfitting, deeper training performs better and shows higher generalization. Hypermarkets cause losses for supermarkets and convenience shops, and in a balanced market, supermarket sales are predicted to decline by 16%.

Savan et al. [6] examine how the COVID-19 epidemic has affected Small and Medium-sized Enterprises (SMEs) that are involved in the food and wholesale market (FGM) in Romania by using three neighborhood proximity shops as a case study. The literature review in this study highlights several challenges facing these businesses, including interruptions in the supply chain, rising expenses, shifts in demand, and digital experiences. Industries experiencing significant declines in demand are also reporting additional challenges that need more thoughtful Decision-Making (DM). The paper emphasizes the significance of demand forecasting for better management DM and the intensifying competitiveness in the Romanian FGM proximity industry. The analysis revealed several factors, such as increased sales in the early months of the pandemic, an increase in the value of the shopping basket, a decrease in individual customers, and a shift in the percentage distribution of product categories. This comprehensive analysis highlights the importance of strategic planning and adaptation to meet these challenges.

Wang et al. [7] observe that since retail businesses provide a wide range of necessities for everyday necessities such as food, clothing, footwear, electrical devices, and office commodities, they are the finest gauges of an industrialized nation's economic status. This research offers merchants a fresh framework to help them accomplish the following objectives: 1) using key financial variables to forecast sales revenues, 2) identifying stable equilibria by monitoring intrastate dynamics between competitive firms, and 3) gaining operational efficiencies through performance evaluation, and suggesting necessary improvements. Data about Walmart, Costco, and Kroger were gathered to guarantee the caliber of the study. The Lasso method was followed to identify important financial indicators. Common variables impacting these three companies' sales numbers are the consumer price index and general wage. Multivariate Adaptive Regression Splines (MARS) and Support Vector Regression (SVR) perform best in the test set and training set, respectively, in sales forecasting. Finally, performance assessment and competitive analysis were conducted using the Lotka-Volterra Model (LVM) and Data Envelopment Analysis (DEA). A mutually beneficial economic relationship was identified between these three institutions. In addition, research results show that Kroger is not operating efficiently but can increase sales more than others in fixed balances.

Yawson and Yamoah [8], authors a book that examined the expansion of retail marketing in developing markets, portraying the industry as a significant investment opportunity. The authors, specifically concentrating on supermarket chains, demonstrate how merchants now have greater options to use micro and macro-marketing strategies due to advancements in infrastructure and technology that have enhanced electronic capacities for data collecting. The authors outline the development of this new marketing period and how it has affected all parties involved, particularly consumers. Considering that Ghana is at the forefront of the use of loyalty cards among African countries, taking this example, for other developing nations, particularly those exhibiting comparable practices, the writers set a standard. Students, researchers, and international businesses who want to learn more about the marketing tactics used by developing countries in sub-Saharan Africa may find this book invaluable.

Miguéis et al. [9] presented efforts to reduce food waste as an important opportunity to increase environmental sustainability. This is crucial as fresh items have far greater loss rates than other food products, such as fresh seafood. In this instance, meeting demand while protecting fisheries also requires waste reduction. To match supply and demand by grocery stores and so avoid the development of food waste, daily fresh fish demand forecasting models are presented as part of this study's effort to advance the creation of more sustainable supply networks. To accomplish this aim, the authors investigated the possibilities of several ML models, including the Holt-Winters statistical model and LSTMNs, FNNs, SVRs, and RFs. Demand censoring was taken into consideration to capture the true demand. Using a case study of a typical shop of a major European retailer, they anticipate the demand for fresh fish to verify the suggested technique. Root Mean Square Error (MSE) (27.82), Mean Absolute Error (MAE) (20.63), and Mean Positive Error (MPE) (17.86) were better in the Long Short-Term Memory (LSTM) networks model than in the baseline and statistical models. ML models made accurate predictions, according to statistical analysis. Implementing this strategy may increase fresh fish species' sustainability and customer satisfaction.

Siljamäki [10] described the Prisma hypermarket chain of S Group in Finland as a decision assistance system. Intense competition has necessitated new business ideas and methods. It was decided that analyzing customer behavior using shopping basket data was important. Customer grouping and profiles were created using multivariate methods. To assist strategic planning, a multi-criteria Decision Support System (DSS) was developed. Then, the DM process can be improved by DSS. This DSS provides immediate assistance in improving DM.

Zheng et al. [11], the analysis of consumer behavior based on e-platform recycling, the single-channel reverse supply chain model (Model-S), and two dual-channel reverse supply chain models (Model-DU and Model-DD) were proposed. The author developed a rigorous theoretical framework for recyclers to establish pricing strategies in diverse conditions by using game theory to the optimal member choices and conducted unique research on channel competition and consumer behavior on e-platform recycling. Increased WEEE recycling

is possible under this model. Therefore, the author recommends that the recycler should create its own channel and use the differential pricing technique (Model-DD). Nevertheless, the e-platform leans more toward Model-S or Model-DU, depending on customer taste and the money WEEE makes from recycling. Moreover, although e-platform preference benefits customers, it harms recyclers and reduces recycling numbers. These findings enhance managerial understanding by providing a theoretical foundation for pricing and channel management strategies in the reverse supply chain.

Joorbonyan et al. [12] proposed a matrix-based approach for Identifying and prioritizing appropriate strategies for customer loyalty in a mass environment. Strategies for prioritizing and choosing strategies are generated from strategic goals and SWOT analysis; the suggested algorithm combines the two. A case study addressing the prioritization of client loyalty techniques for a women's clothes business in Ramsar City used the suggested strategy. The issue owner's assessments were used to identify the available strategies, influential environmental factors, future scenario definitions, and how well strategies performed in various environmental settings. Strategies that consider important environmental factors (such as the value of the national currency, availability of raw materials and markets, changes in lifestyle, investment security, government-private sector relations, and the rate of technological change) rank highest. The ranked environmental advertisements, collaborative production, and customer relationship management followed. Priority strategies reduce environmental hazards and their effects on businesses, according to the results of the suggested method, which considers the country's expected future circumstances.

Zhang and Shi [13] suggest a study plan for a sharing model of impulsive purchases based on user characteristics and a previously published work that presents certain aspects. A data analysis based on AMOS23.0 and SPSS24.0 is used to assess the model. The findings demonstrate that the key elements of vividness, media richness, and interaction positively impact social presence. Consequently, social presence directly affects impulsive purchasing behavior in the variable relationship. This finding adds to the theory of the marketing theory model and has practical implications for business marketing strategy.

Ghaforiyan et al. [14] discussed the Antifragility Analysis Algorithm (AAA) for Identifying and Prioritizing Antifragile Tourism Strategies in a Neutrosophic Environment. Neutrosophic Sets (NSs) were used to gather the verbal assessments of experts; these sets successfully handled ambiguity and uncertainty. The author first compiled a list of eleven potential approaches with the assistance of industry professionals. The author outlined thirteen potential futures and one present by identifying five significant environmental indicators and conceivable conditions for each. The next step was to use NSs to evaluate how well each strategy performed in each indicator state. Then, the antifragility scores of the strategies were calculated, taking the future situations into account. According to the data, all proposed solutions are antifragile; thus, putting them into action might improve things even more than they are right now. According to the results, starting with market research, building infrastructure, including the community, diversifying, and monitoring is the best approach. The next stage should include implementing strategies for destination branding, halal tourism, and crisis management. The last stage is when the remaining plans may be put into action.

Research by Sharifi and Yazdani [15] examined how the Cinere Company's social identity, perceived value, and consumer satisfaction mediated the impact of marketing efforts conducted on social media platforms on the intention to make a purchase. The Cinere Cosmetics Company has an infinite consumer base. Thus, 384 individuals were chosen randomly as samples. The study questionnaire developed and validated was used to gather data, and its reliability and validity were evaluated. In terms of goals and gathering descriptive data, this study is practical. The data was analyzed using SPSS and Smart PLS software. The findings demonstrate that marketing initiatives centered on social media have a favorable and substantial impact on social identity, perceived value, customer satisfaction, intention to buy, intention to persevere, and intention to participate. Customer satisfaction is favorably impacted by social identity and perceived value as well. The intention to buy, the desire to continue, and the intention to participate are all positively impacted by customer satisfaction.

Kuang et al. [16] introduced Deep Neural Networks (DNNs) and Recursive Neural Networks (RNNs) for sentiment classification in product reviews. The author uses a resampling strategy to fix the dataset's positive/negative sample imbalance in social network data by boosting minority class samples and lowering majority class samples. The author assesses the method by analyzing data from four product categories sold on Amazon: apparel, automobiles, luxury items, and home appliances. The experimental findings show that our suggested method works effectively for digital marketing sentiment analysis of product reviews. In addition, there is a 5% performance gap between the baseline RNN and the attention-based RNN algorithm. It is worth mentioning that the survey uncovers differences in customer attitudes toward various items, namely regarding pricing and look.

Fakhrehosseini and Kaviani [17] described the exchange rate fluctuations induced by the financial crisis and the implications for Iran's current account deficit using the Error Correction Model (ECM). The results show how financial crises affected Iran's current account deficit, how exchange rate volatility affects economic stability, and how complex macroeconomic connections shift during budgetary uncertainty. The study highlights the need for strong monetary and fiscal policies to handle economic vulnerabilities and prepare for financial shocks.

Zhang et al. [18] investigated Corporate Social Responsibility (CSR) and Earnings Persistence. The statistical population used for this purpose includes 714 firm-year observations spanning 2014–2020 (7 years). The present work used a multivariate regression approach based on panel data analysis to examine its given hypothesis empirically. According to the author, operational efficiency moderates the positive and substantial relationship between CSR and profit persistence, but financing cost is irrelevant. Research in this area has mostly concentrated on underdeveloped nations. Global perspectives are crucial, and the study contributes to the expanding body of information on sustainability.

Nejati et al. [19] suggested the Neural Network-Based Hybrid Method for Added Damper and Stiffness (ADAS) damper optimization in absorption of earthquake energy. Therefore, each seismic behavior is modeled for a 15-story steel structure with steel bracing in at least four reinforcing modes and an ADAS damper. The research on high-rise buildings also covers finding the best reinforcement condition using dampers, which are also used as selection criteria for these structures. Here, at least 10 accelerograms are used using Incremental Dynamic Analysis (IDA). Here, structural design, non-linear analysis, OpenSees, and Matlab optimization are all handled by Etabs. Diverse damper configurations were found to cause buildings to behave in diverse ways. The study's modeled structures exhibited diverse behaviors depending on the mirror type, resulting from the dampers' varying hardness and performance.

Ghasem Abadi [20] proposed the ML-Based Authentication of Banknotes. ML methods were employed to detect and classify counterfeit cash, and this is the main focus of the study. The research uses a dataset that includes both real and fake banknotes and applies several classification methods for constructing a strong model for automated detection. A comprehensive banknote authenticity study was employed. Important properties, including texture, color distribution, and security aspects, are retrieved. Improved security measures for financial transactions and less economic fraud are possible outcomes of the suggested system's encouraging accuracy in differentiating legal tender from counterfeits.

Darwish [21] recommended the data-driven DL approach for the Remaining Useful Life (RUL) of rolling bearings. A DL model that uses a Convolution Neural Network (CNN), LSTM, and Attention Mechanism (AM) was employed in this study to enhance the accuracy of the RUL of rolling bearings. CNN initially evaluated the input data in the temporal domain to extract features. Based on the input sequence's meaning or content, an AM is used to align the input and output sequences. Then, two LSTM layers are used to record complex temporal correlations and generate more abstract data representations. Finally, the Fully Connected (FC) layer makes the predictions. The author compares the suggested model's performance to other DL models and uses the IEEE PHM 2012 Challenge dataset to assess the model's usefulness. Regarding

forecasting rolling bearing RUL, the proposed CNN-ALSTM model outperformed all other models tested in the experiments.

Mohamed and Gharib [22] construct a new LSTM Predictive Analysis Model (PAM) for Cryptocurrency Behavior. Building a PAM with LSTM capability to accurately forecast Bitcoin's price the next day and discover price-influencing characteristics is the primary objective of this work. The author uses a thorough technique in building PAM to investigate minute-to-minute Bitcoin data for temporal correlations via data exploration, advanced ML methods, and preprocessing. Providing in-depth data necessary for long-term market investment, our results show that the LSTM model is excellent at predicting bitcoin behavior.

Mohamed [23] discussed DL-based organizational DM. Organizations, especially those in Egypt, may use the findings to further their development objectives by capitalizing on the revolutionary possibilities offered by these technologies, as the research reveals. The author outlines possible avenues for future study, focusing on new trends, technical developments, and upcoming technologies. This poll is a great tool for academics, politicians, and practitioners interested in using DL to make empowered, data-driven, and educated choices as an organization in this digital age.

Choi et al. [24] deliberated ML and IoT for consumer behavior analysis. This paper shows the use of five machine-learning methods in processing data from the 2019 MCR survey (N=3,922). Concerning forecasting consumers' uptake of wearable gadgets, the random forest model outperforms the others. This strategy has helped us identify 17 key factors that will impact adoption. The study's results point to middle-aged and older women as the most likely to buy wearable technology. These consumers are defined by their high spending relative to their income and their high criteria for consumption, which include consideration of features, design, pricing, shopping efficiency, and brand reputation. This study was one of the first to use ML for consumer targeting in wearable devices, contributing to advertising and marketing literature.

Jain et al. [25] presented artificial intelligence consumer behavior. By using bibliometric and framework-based methodologies to 107 papers on artificial intelligence and cognitive bias, this article hopes to fill this knowledge vacuum and provide light on the field's current state, including publishing patterns, prevailing theories, techniques, antecedents, choices, and consequences. The review's primary contribution is its conceptual framework for ongoing studies by highlighting groups of related study areas. All of these groups or topics have to do with how AI interacts with different aspects of consumer behavior, such as how they trust and accept it, how they engage with it, their attitude and personality, how they make decisions, and how they embrace it. To further theory development and its societal and economic ramifications, this theme framework and TCM-ADO analysis provide avenues for further study.

Yahui Liu et al. [26] ML algorithm presented for customer choice prediction. This paper presents significant interaction effects among three factors: 1) the amputation mechanism and imputation techniques, 2) imputation and imbalance treatments, and 3) imbalance treatments and classification algorithms, which adds to the knowledge already present in the literature. The author experimentally demonstrates that Random Forest outperforms logit, SVM, and DT among various categorization algorithms using three UCI ML Repository consumer behavioral datasets. In addition, when it comes to real-world datasets, Logit, the most used classification algorithm, has the biggest problems with imbalance. In addition, regardless of the missing value mechanism or imputation method, Metacost is the optimal imbalance therapy.

Yaiprasert and Hidayanto [27] proposed the integration of artificial intelligence-driven ensemble ML to optimize cost strategies within the logistics industry. This study aims to learn how well AI-driven ensemble ML can simulate threshold cost data from businesses to find the best ways to mitigate such costs. As ML algorithms, three ensemble ML approaches are used to find patterns and correlations in the cost data for strategic choices. The dataset has 6561 possible tuples. The uniqueness of this initiative is in showing how simulated data might improve companies' cost-saving methods. Business owners and marketing and production staff may benefit from this study's findings on the potential of ML applications, which adds to

the current literature on AI and ML uses in business. Some of the many sectors that stand to benefit greatly from this study's conclusions include retail, logistics, and transportation.

Paldino et al. [28] presented an analysis of the significance of variety and Ensemble Learning (EL) in the detection of credit card fraud. Properly capitalizing on historical information is essential. To facilitate faster adaptation to changes, the author provides a learning technique based on diversity-based EL that enables the preservation and reuse of prior notions. The trials compare different learning strategies and use several state-of-the-art diversity metrics. Based on data extracted from two genuine datasets supplied by the industry leader, Worldline, the author evaluates the efficacy of the suggested learning technique. These datasets cover two European nations and comprise over 30 million and 50 million transactions.

The article presents a new model called the Bootstrap Aggregated Neural Regressor (BANR); however, it should differentiate this method from others in the literature. To tackle the problems of overfitting, poor interpretability, and susceptibility to noisy data prevalent in current models, BANR combines the advantages of NNs with the bagging methodology in a novel way, unlike ensemble techniques or classic neural networks. A good example is how BANR trains multiple NNs on different bootstrapped samples and aggregates their predictions to reduce variance and enhance robustness. This helps with typical neural network models' overfitting problems, which can be caused by their complexity and dependence on large, clean datasets. On top of that, BANR uses deep neural architectures to model complicated, non-linear interactions in high-dimensional consumer data, which is more successful than typical ensemble models that may use weaker learners, such as DTs. Through the intentional integration of these components, BANR presents a methodological leap forward that enhances the accuracy of predictions and their practical relevance in analyzing customer behavior.

3 | Proposed Method

BANR is suggested in this study to understand consumer behavior and purchasing preferences. This model combines EL and DL techniques for accurate results. Multiple lightweight NN can be trained using the bootstrap sampling method by BANR. This method facilitates the effective operation of every NN. The BANR model has been developed to analyze and understand consumer behavior. Various sampling techniques and handling large data sets facilitated data cleaning and analysis. Then, the model becomes more effective and robust by applying AT in BANR. Understanding customer behavior across different data sources and volumes is considered the main objective of BANR. This model can identify patterns in consumer behavior. It also offers effective techniques for data analysis. Improving businesses and marketing strategies can be attained by the BANR.

3.1 | Core Neural Network Model

Separable CNNs are a type of CNN architecture designed to increase computational efficiency while maintaining the same level of performance in applications like image recognition, object detection, and segmentation. Efficiency is achieved by separating the filtering process by breaking down the usual convolution process into two distinct operations: depthwise convolution and pointwise convolution.

Input layer: this layer is the starting point of the data. Here, the size of the input data is specified by self.input_dim.

Dense layer: each hidden layer has a Dense layer. It consists of unit neurons. activation='relu' means that the ReLU (Rectified Linear Unit) activation function is used

ReLU: in NN AF, the ReLU is used. The ReLU AF can be represented as, $f(x)=max(0,x)$

The ReLU function zeroes out all negative inputs and averages the positive ones. In this way, ReLU overcomes linear network limitations. ReLU increases training speed because the derivative of this function is either 0 or 1. This helps to overcome the gradient vanishing problem so that deep NNs can learn effectively.

Batch normalization: batch normalization is used after each dense layer. This is mainly used to increase model training speed and improve stability.

Dropout: the hidden layer is followed by the Dropout layer; this technique mitigates overfitting by stochastically removing some neurons throughout the training process. The dropout rate is determined by self.dropout_rate.

Dense output layer: finally, the output layer is a Dense layer that has only one output neuron as it is designed for the regression task.

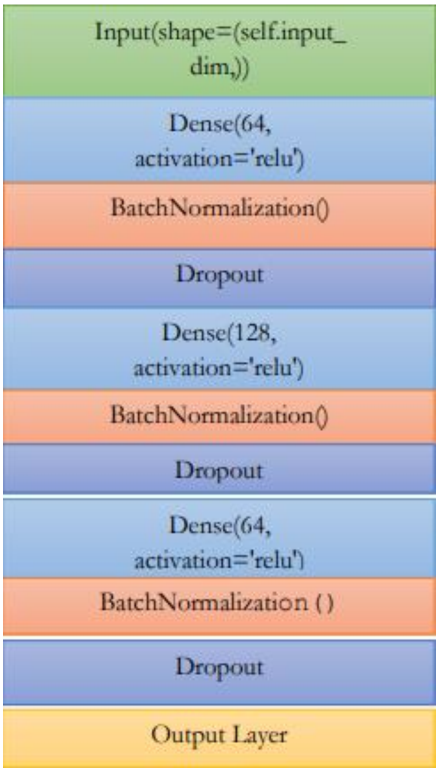

Fig. 1. Neural network model.

The input and output layers generated as a model by the tf.keras.models are shown in Figure 1. Model function. When compiling the model, the optimizer and loss function are explicitly defined. Adam optimizer and MSE loss function are used here. Adam optimizer is known for its fast and efficient training. For optimal implementation, BANR models need many preprocessing stages. Imputing missing numbers with the median or mean is one example of how outliers are handled during data cleaning, which also addresses missing values, fixes mistakes, and handles outliers. The features are then either normalized or standardized so that they all contribute equally; the former scales them to a range between zero and one, while the latter transforms them to have a mean of zero and a standard deviation of one. One-hot and label encoding methods transform categorical data into numerical forms. Feature selection and engineering are also performed to choose useful features and generate new ones that may capture critical patterns. Random splitting or k-fold cross-validation are common methods for dividing the dataset into training and testing sets, which are used to assess the performance and generalizability of the models. The last step is to employ techniques like resampling or changing class weights to ensure all classes are represented equally. To ensure that BANR can provide trustworthy findings, these preprocessing procedures are vital for getting the data ready. BANR is great for dealing with complicated, high-dimensional consumer data since it uses the bagging strategy to decrease variance and overfitting. They showed how BANR's technique enhances consumer behavior research's predicted accuracy and resilience compared to alternative approaches like classic NNs or ensemble methods like random forests.

Adam optimizer: Adaptive moment estimation (Adam) optimizer is a widely used optimization algorithm in DL. Adam works based on Stochastic Gradient Descent (SGD) but uses two maintaining moment concepts: i.e., exponential moment of gradient and exponential moment of gradient squared. This approach has the advantage of having a stochastic nature of the gradient, i.e., it provides a dynamic adjustment of the learning rate. The main advantage of the Adam optimizer is that it fits with less data for highly significant and global optimization. It works easily and efficiently on different datasets and optimizes with low memory usage. Thus, the Adam optimizer stands out among the extensively used and well-liked optimization techniques for DL models.

MSE is a commonly used statistic to assess regression models' performance. The mean of the squared values computes the discrepancy between the recorded and true values. Computing the square of the difference between the predicted and actual values gives the MSE calculation for each data point and dividing that sum by all data points.

3.2 | Adversarial Training

Adversarial Training (AT) is used in NNs and plays a significant role in enhancing the robustness and security of models. This process trains the model with a regular dataset and adversarial examples. These inputs can cause the model to predict incorrectly. This model helps protect the model from such fraudulent experiments. The concept, process, and importance of AT are explained below. The concept of AT is to challenge the model appropriately. Typically, using small errors or fluff in neural networks, some specially designed inputs will cause the model to predict incorrectly. Such inputs are called adversarial examples.

Creating adversarial examples is an important and complex process. This is possible by making small changes to the normal input. For example, data can be falsified by changing the values to some low values. These changes are invisible to us, but they create major problems for the model.

The process of AT:

I. Input creation: basically, adversarial examples are created along with normal input data. These examples are designed to cause small distortions to the model.

II. Model training: training the model with these generated adversarial examples. Incorporating both normal and adversarial data makes the model more robust and secure.

III. Validation: continuously testing the model during training to see how it performs on adversarial examples, thus increasing model accuracy and safety.

AT mainly helps in making the models more robust. This is important in real-world applications. For example, it is vital in financial transactions, healthcare, and security applications. This method helps models operate more reliably by protecting them from adversarial attacks.

3.3 | Meta-Learner for Weight Optimization

Meta-learning is an advanced method of ML. It uses one model to train another model. Using the idea of a meta-learner, better results can be achieved in EL and multi-model applications. A meta-learner is a model designed to improve and optimize the performance of the main model. In meta-learning, a base learner is trained on many data samples, and a meta-learner is trained using the output of these base learners. The ensemble model predictions were employed in this approach, as it offers accurate results.

The meta-learner in the BANR offered the final prediction. The predictions of the base learners were used to attain accurate outcomes. The meta-learner is constructed as follows:

I. Base learners: the base learner is ANN, and it has been trained on various samples. When exposed to various data, distinct patterns were identified, and distinct predictions were made by the base learner.

II. Meta-learner input: NN, as the meta-learner, has one IL and one dense layer. The IL accepts the predictions made by the base learners and then combines them to create a single output.

Meta-learner algorithm

Step 1. Data sampling: the data set is divided into different samples. A base learner is trained on each sample.

Step 2. Base learner training: a basic learner is trained on each sample. Prediction of the base learner is collected.

Step 3. Meta-learner input: the meta-learner uses the base learners' predictions as input.

Step 4. Meta-learner training: these predictions are used to train a meta-learner.

Step 5. Final prediction: after completing training, the meta-learner merges the primary learners' predictions and provides a final prediction.

3.4 | Training Process

The training process of BANR uses basic learners and meta-learners in a complex and structured manner. The training process is described in detail through the steps of theory and algorithm.

I. Basic learners training:

- *Training several base models (Base Learners) on different data samples.*
- *By training each basic model with different samples, different patterns are identified in their predictions.*
- *This method increases the diversity in the model and improves its accuracy.*

II. Adversarial training:

- *Conducting AT on each basic model.*
- *Making the model more robust by introducing small perturbations to the data.*

III. Meta-learner training:

- *Collecting predictions from all basic models.*
- *These predictions are fed as input to the meta-learner.*
- *Accurately offer the final forecast after training the meta-learner. The algorithm steps include:*

IV. Starting with basic models:

- *Create basic models and place them on an empty list.*

V. Data sampling:

- *Several samples from the main data set were taken.*
- *Training different basic models on each sample.*

VI. Basic models training:

- *Training each basic model on sample data.*
- *After each training session, AT on that model will be conducted.*

VII. Collection of predictions:

- *Collecting predictions from all basic models.*
- *Storing these predictions in a meta-features matrix.*

VIII. Structure of meta-learner:

- *Building a meta-learner.*
- *This meta-learner integrates the predictions from all the underlying models.*

IX. Meta-learner training:

- *Training a meta-learner with meta-features and original labels.*
- *After training is completed, the meta-learner's weights.*
- *Thus, the BANR training process provides efficient final predictions by the initial and meta-learners.*

3.5 | Gradient Boosting Aggregation

Gradient Boosting Aggregation is a powerful method in ML that integrates predictions from multiple base models to provide more accurate results. In the BANR model, an EL technique indicates gradient boosting uses several fundamental models to provide precise results. Each primary model uses a later model to fill in its gaps. Each basic model is not trained only once. The initial model results are then used to refine the model. The final prediction is more accurate by gradually correcting the errors in each model.

Initially, the basic model is trained on data and makes predictions. The difference between this prediction and the actual values (residuals) is gradually considered, and the model is trained. Each subsequent model is trained to correct errors in the previous model. In this way, all the models combined provide a comprehensive prediction. All preliminary model predictions are combined to make the final prediction. In this final prediction, each model's prediction is not identical but is useful in correcting its errors.

In the BANR model, the Gradient Boosting Aggregation method is used as indicated below:

I. Primary learners: several basic NNs are trained on different samples.

II. Models predictions: each neural network makes its prediction. A neural network is then used to correct for errors in these predictions.

III. Meta-learner: a meta-learner uses predictions from all basic neural networks. The meta-learner integrates these predictions and provides an accurate final prediction.

The novel features of the proposed framework as follows:

I. Meta-learning for weight optimization: use a meta-learning approach to dynamically adjust the weights of individual NNs based on their performance across different subsets of the data.

II. AT for robustness: incorporate AT to make the model robust to data perturbations and adversarial attacks.

III. Attention mechanism: include an AM so that the model may concentrate on the portions of the input characteristics that are most relevant.

IV. Gradient boosting aggregation: instead of simple weighted averaging, use a gradient boosting method to aggregate the predictions of the individual neural networks.

V. Self-ensembling: utilize self-ensembling, where each neural network learns from the training data and incorporates knowledge from other networks' predictions.

Using BANR to examine demographic information, online activity, and past purchases, the model might categorize consumers into several categories, such as price-sensitive, repeat purchasers, or high-value customers. The store may use the data to create segmented marketing efforts, such as rewarding loyal

customers with exclusive offers or providing price-sensitive clients with customized discounts. The accuracy of BANR's personalized recommendations might be enhanced by studying trends in user interactions with items, such as click-through rates, time spent on product pages, and past purchase history. For instance, BANR can enhance the ability to predict and suggest outdoor goods. For customers who often buy hiking boots or camping gear, this means higher conversion rates and more satisfied consumers.

4 | Experimental Results

The Customer Shopping Trends dataset is available on Kaggle [29]. It provides comprehensive data about consumer shopping behavior and patterns. This dataset is designed to help businesses and researchers understand consumer preferences, purchase volumes, and shopping trends. This dataset analysis will obtain useful information to enhance product placements, marketing strategies, and consumer experience. Various factors about consumer purchasing behaviors are included in this dataset, which is vital for companies who want to learn more about their clientele. Customer demographics such as age, gender, purchase total, payment method preference, buying frequency, and review score are part of the package. The package also includes data about the products bought, how often, during which seasons, and how customers interacted with promotions. Businesses seeking to utilize data-driven insights for improved DM and customer-centric strategies may use this dataset, which contains 3900 records, as a basis. This dataset uses a 70-30 train-test split, employed k-fold cross-validation with k=10.

This work uses this dataset to analyze consumer behaviour and shopping preferences. Businesses can obtain insight into client preferences across various demographics by evaluating parameters such as customers' age, gender, income, and spending score. The information can address queries like which gender buys particular things at a higher rate or which age group spends the most. Product category and purchase amount are features businesses can use to accomplish marketing objectives and enhance product placement. Seasonal variations in shopping patterns can be recognized, and future demand may be predicted by examining transaction records. As a result, the Customer Shopping Trends dataset is an effective resource for learning about buying preferences and customer behavior. These are the features of the dataset:

- *Customer ID: a unique identifier for each customer.*
- *Age: the age of the customer*
- *Gender: customer's gender (Male/Female).*
- *Item purchased: a product acquired by the consumer.*
- *Category: selected category of the purchased item.*
- *Purchase amount (USD): the amount spent on the purchase in dollars.*
- *Location: place of purchase.*
- *Size: the size of the purchased item.*
- *Color: the color of the item that was bought.*
- *Season: season of purchase.*
- *Review rating: the customer's rating for the product they purchased.*
- *Subscription status: whether the user has a subscription (yes/no).*
- *Shipping type: the shipping type selected by the user.*
- *Discount applied: whether a discount has been applied to the purchase (yes/no).*
- *Promo code used: whether a promo code was used in the purchase (yes/no).*
- *Previous purchases: excluding the current transaction, the cumulative count of prior transactions conducted by the user in the store.*
- *Payment method: the payment method of preference for the user.*
- *Frequency of purchases: consumer purchasing frequency (e.g., once a week, once a fortnight, once a month).*

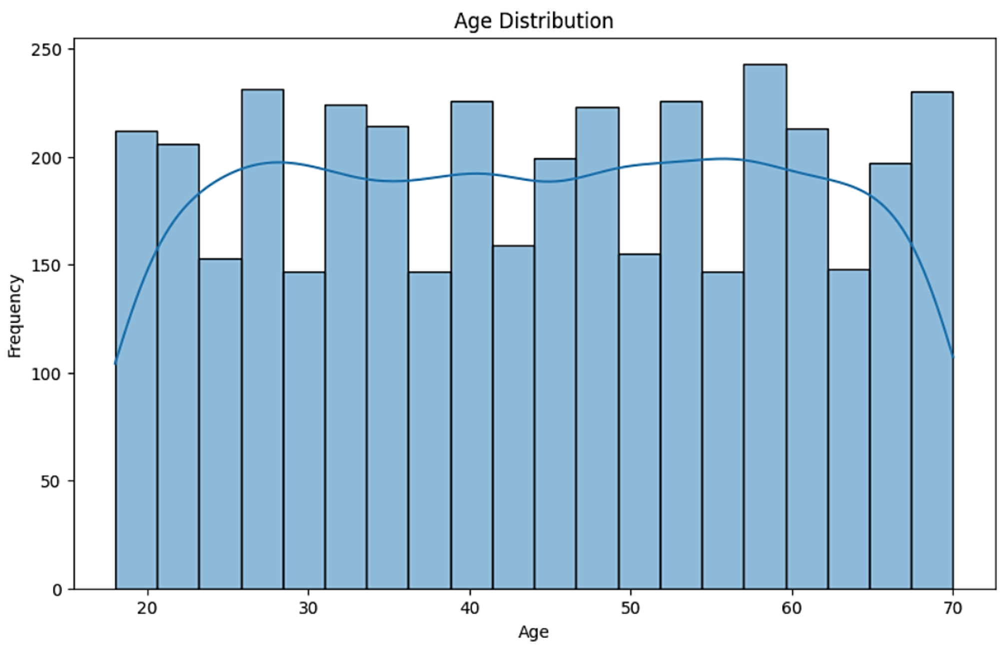

Fig. 2. Age distribution in the dataset.

Fig. 2 shows the age distribution of users in the dataset. On the x-axis are user age groups, and on the y-axis are the numbers. This figure helps to understand how the age of consumers is standardized. Using this data, businesses can understand the preferences of different age groups. For example, details of which age groups spend the most and which age groups prefer which products. Age distribution data is a key part of demographic analysis and in tailoring marketing strategies.

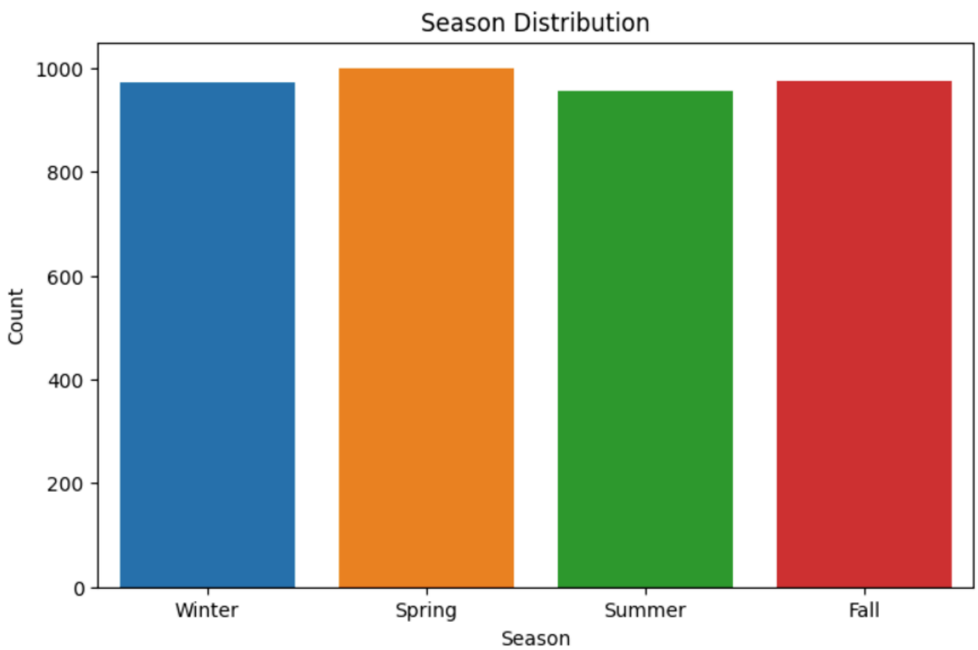

Fig. 3. Sales in different seasons.

Fig. 3 shows the sales during different seasons. On the x-axis are the seasons (spring, summer, fall, winter), and on the y-axis are the number or amount of sales for each season. Through this figure, the purchasing behaviour of consumers can be understood based on seasons. For example, which season has the highest sales and which season has the lowest sales can be studied. Businesses can use this data to set seasonal promotions, stock management, and other strategies.

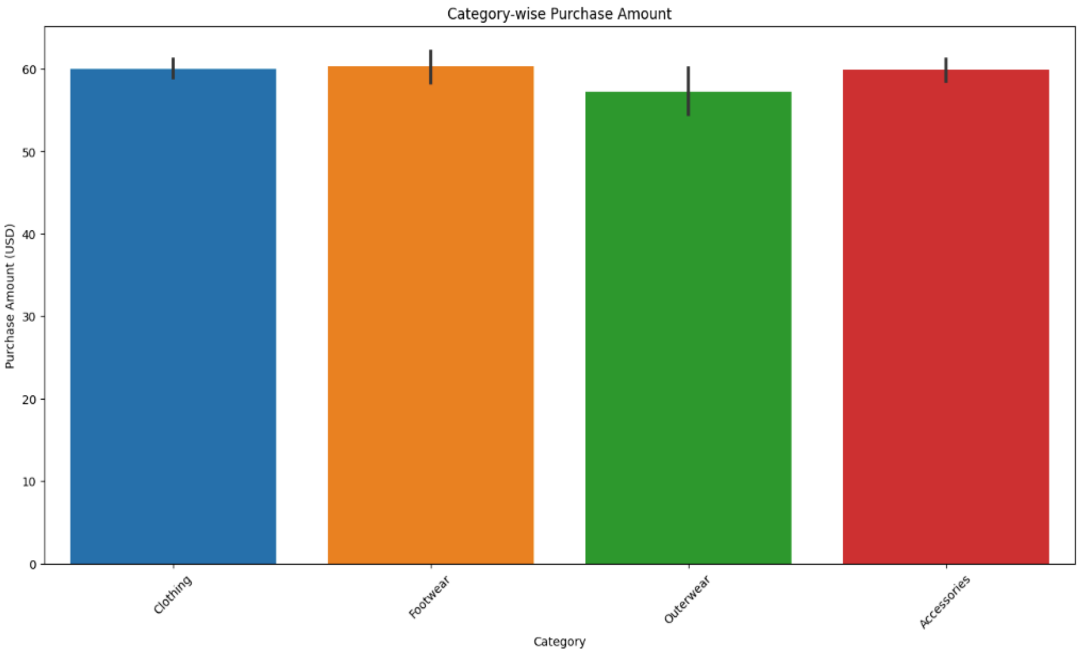

Fig. 4. Amount spend in different categories.

Fig. 4 shows the amount spent by consumers in different product categories. On the x-axis are product categories (e.g., clothing, electronics, food), and on the y-axis is the amount spent in each category. This figure lets businesses know which product categories are spending the most. With this information, businesses can improve their product lines and marketing strategies, focusing more on products that generate more revenue.

Fig. 5. Number of times discount applied.

Fig. 5 shows the number of transactions where the discount has been applied. On the x-axis is whether the discount is applied, and on the y-axis is the number of transactions the discount was applied to. This figure shows how much customers use the discounts and how much it affects sales. This information helps businesses improve their discount and promotion strategies.

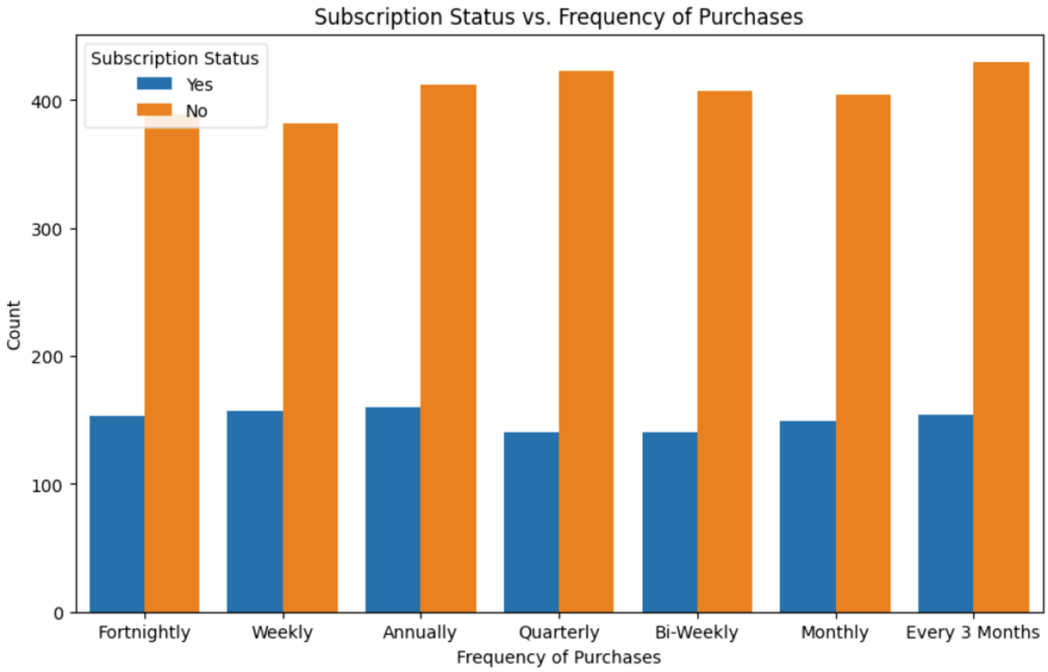

Fig. 6. Subscription status concerning the frequency of purchases.

Fig. 6 shows the frequency of user purchases in terms of subscription status. On the x-axis is the subscription status (yes, no), and on the y-axis is the number of times users have purchased based on their subscription status. This figure shows how often users with a subscription buy and how often those without a subscription buy. For example, if this figure indicates that users with a subscription purchase once every week or once every month, non-subscription users are likely to purchase less frequently. This information allows businesses to improve their subscription programs and increase customer loyalty and purchase frequency. Businesses can create effective marketing strategies by understanding the relationship between subscription status and purchase churn.

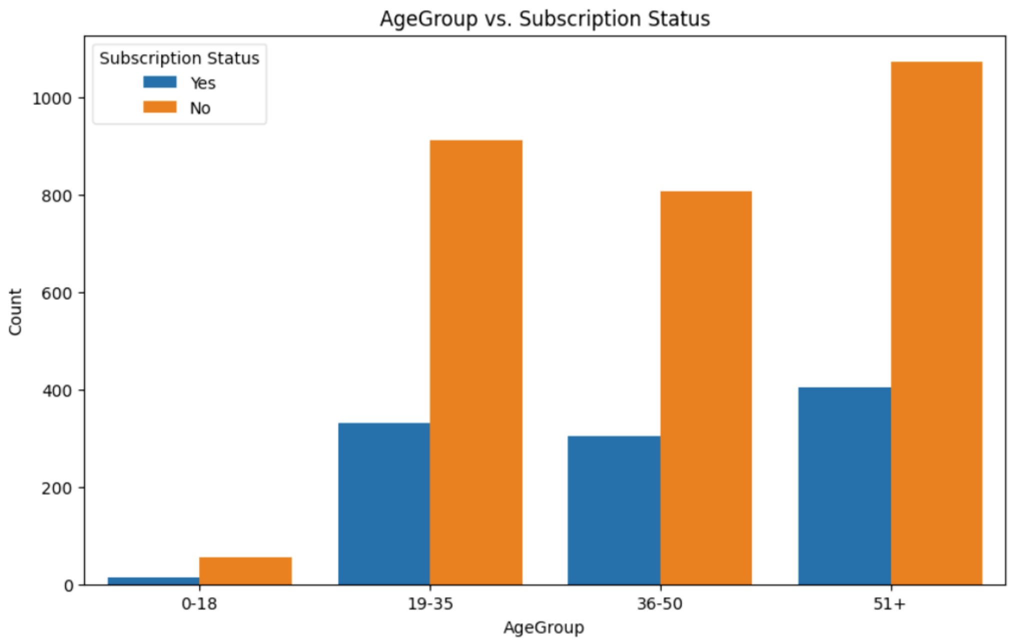

Fig. 7. Age group concerning subscription status.

Fig. 7 shows the age group of users concerning subscription status. On the x-axis are the age groups (e.g., 0-18, 99-35, 36-50, 51 above), and on the y-axis are the number of subscribers in each age group. By this figure,

we can understand the users who take subscriptions based on age. Businesses can use this data to promote age-based subscription offers and increase customer engagement.

Table 1. Confusion matrix.

	No	**Yes**
No	687	5
Yes	2	281

Through this matrix, the accuracy of the model and its errors can be clearly understood in *Table 1*. By having 687 True Positives (TP) and 281 True Negatives (TNs), it is clear that the model is considered correct in a high percentage. With 5 False Positives (FPs) and 2 False Negatives (FNs), it can also be known that the model sometimes makes mistakes. Using the statistics in this matrix, necessary modifications can be made to improve the model's performance.

Additional Parameters

I. Precision:

- *Class 0: 1.00.*
- *Class 1: 0.98.*

II. Recall:

- *Class 0: 0.99.*
- *Class 1: 0.99.*

III. F1-score:

- *Class 0: 0.99.*
- *Class 1: 0.99.*

IV. Support:

- *Class 0: 692.*
- *Class 1: 283.*

V. Macro average:

- *Precision: 0.99.*
- *Recall: 0.99.*
- *F1-Score: 0.99.*

VI. Weighted average:

- *Precision: 0.99.*
- *Recall: 0.99.*
- *F1-Score: 0.99.*

The overall accuracy of the model is 99%.

This research mainly analyses consumer behaviour and shopping preferences using the BANR model. The BANR model, using several lightweight neural networks, helps predict consumer behavior accurately. In this analysis, I explain how the current findings fit this topic.

BANR model working procedure:

I. EL: BANR uses a bootstrap sampling method using several lightweight neural networks. Each network is trained on different samples, making the model more stable and efficient.

II. AT: the BANR model uses AT to incorporate small distortions, making the model more robust. This prepares the model to deal with different types of data gaps.

Meta-learner: integrating results from basic NNs using meta-learner. By this method, the results of all networks are converted into a single final prediction.

The BANR model achieved 99.28% accuracy. This statistic indicates that the model correctly accounts for a high percentage, which helps predict consumer behaviour and shopping preferences. The results with TP (687) and TN (281) show that the BANR model is correct in most cases. Due to FPs (5) and FNs (2), although there are some errors, their impact is low. The values of 0.99 in Precision, Recall, and F1-Score indicate that the BANR model performs very accurately and reliably.

The BANR model accurately predicts consumer behaviour and helps businesses improve their marketing strategies.

By employing several NN and meta-learners, this model attained high accuracy in DA. Effectively managing different datasets and robustness was enhanced by AT.

The complex, non-linear correlations were effectively captured, and it also eliminates overfitting problems. Various insights into consumer preferences and consumer behaviors were completely understood by the BANR model when compared to previous models. Marketers and organizations developed more precise prediction models. BANR has the potential to be flexible in managing large-scale and high-dimensional datasets. It will also help in analyzing consumer data from e-commerce sites, social media, and other digital platforms.

Because of the results, which show that advanced ML techniques like BANR may link theoretical models of consumer behavior with real-world applications, the business may be able to make more data-driven decisions. More personalized methods will contribute to enhancing consumer behavior. When comparing this method to other standard approaches, this suggested method will boost customer engagement and retention.

By using a bagging strategy, BANR reduces the processing resources needed for classic deep NNs and their vulnerability to overfitting. To reduce training time, BANR trains many NNs on smaller, bootstrapped subsets of data instead of one large model. This allows for parallelization of training over multiple CPUs or GPUs. Due to the complexity of NNs and the requirement to train many models, BANR may still demand substantial computing resources compared to simpler models like random forests or gradient-boosting machines. Regarding scalability, BANR is superior to models like support vector machines or DTs when handling large-scale, high-dimensional datasets. This is because NNs are inherently flexible. It makes BANR more adaptable to complex scenarios involving consumer behaviour analysis. BANR scales more efficiently in practice than several state-of-the-art models, requiring more initial computing resources. This is due to its ability to parallelize training and successfully handle large datasets.

5 | Conclusion

This study aims to overcome the limitations of the existing models, as it fail to comprehend consumer preferences. Several lightweight NNs trained in bootstrap sampling and AT techniques were employed in this method. By employing Meta-learning and AT, consumer behavior was effectively understood, and the

suggested framework offered a robust solution. The consumer behavior was effectively analyzed, and predicting purchase decisions can be done by the BANR model. The ability of the BANR model to analyze and predict consumer behavior and buying preferences was demonstrated in this study. The model accurately classified TP and TN samples with 99.28% accuracy. This BANR framework attained an F1-score of 0.99, recall of 0.99, and precision of 0.99. These values indicated the accuracy and reliability of the framework. By employing AT and meta-learning strategies, consumer behavior was effectively and precisely understood by this model. The significance of the BANR model in accurately predicting consumer behavior was demonstrated in this study. The recommended BANR has a number of issues, including sensitivity to the quality and variety of the data, which may limit its applicability in some scenarios. The model might not be appropriate for usage in environments with limited resources because of its high computational complexity. Future research could address these limitations by strengthening the model through reinforcement learning, simplifying it through the use of strategies like AM or significant feature analysis, and figuring out approaches to allow real-time adaptation so the model can adjust and learn in real-time in response to new consumer data.

Author Contributaion

Gurunadham R: Conceptualization, writing-reviewing and editing, data maintenance. And Dr. V. B. Narasimha: Methodology, formal analysis, funding procurement.

Funding

The authors did not receive financing for the development of this research.

Data Availability

The Customer Shopping Trends dataset is available on Kaggle.

Conflicts of Interest

The authors declare that there is no conflict of interest.

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